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RESEARCH PAPER

Application of remote sensing, an artificial neural network leaf area model, and a process-based simulation model to estimate carbon storage in Florida slash pine plantations.

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Abstract: Carbon sequestration in forests is of great interest due to concerns about global climate change. Carbon storage rates depend on ecosystem fluxes (photosynthesis and ecosystem respiration), typically quantified as net ecosystem exchange (NEE). Methods to estimate forest NEE without intensive site sampling are needed to accurately assess rates of carbon sequestration at stand-level and larger scales. We produced spatially-explicit estimates of NEE for 9 770 ha of slash pine (*Pinus elliottii*) plantations in North-Central Florida for a single year by coupling remote sensing-based estimates of leaf area index (LAI) with a process-based growth simulation model. LAI estimates produced from a neural-network modeling of ground plot and Landsat TM satellite data had a mean of 1.06 (range 0-3.93, including forest edges). Using the neural network LAI values as inputs, the slash pine simulation model (SPM2) estimates of NEE ranged from -5.52 to 11.06 $Mg \cdot ha^{-1} \cdot a^{-1}$ with a mean of 3.47 $Mg \cdot ha^{-1} \cdot a^{-1}$. Total carbon storage for the year was 33 920 t, or about 3.5 tons per hectare. Both estimated LAI and NEE were highly sensitive to fertilization.

Keywords: artificial neural network; leaf area; carbon exchange; slash pine; NEE; forest carbon

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Introduction

The potential consequences of global climate change are now widely accepted and are a matter of grave concern to policy makers (King 2004). The regional balance of greenhouse gas fluxes is influenced by anthropogenic and natural sources and sinks. In order to limit global warming to the widely accepted standard of 2ºC or less, large reductions in net emissions are required (Meinshausen et al. 2009). One approach to reduce net carbon emissions from human activities is to manage forests for enhanced carbon sequestration. These strategies may include afforestation, avoiding forest destruction and degradation, and altered silviculture (Ray et al. 2009).

Flows of carbon within forest ecosystems are complex, and estimates of net carbon storage (or NEE; Net Ecosystem Exchange) for a landscape are difficult to produce yet are needed to optimize sustainable production and understand the effects of forest management (Waring and Running, 1998). Local estimates of carbon exchange are typically made through eddy flux systems (e. g. Powell et al. 2008) or destructive sampling. NEE may also be estimated through simulation modeling, a potentially scalable approach, if the system is reasonably homogenous, using a well verified model (Turner et al. 2004). The primary biophysical parameter needed for NEE simulations is leaf area index (Cropper & Gholz 1993) which may be assessed from satellite imagery using regression or neural network modeling (Shoemaker & Cropper 2008). In this work we couple simulation modeling of NEE with remote assessments of LAI to produce estimates of carbon exchange for a large industrial pine plantation, a method which eliminates intensive site measurements and would therefore be useful for managing mitigation systems at landscape scales.

The SPM-2 model (Cropper & Gholz 1993; Cropper 2000) estimates NEE for slash pine (*Pinus elliottii*) plantations, a dominant plantation type in Florida and the subject of several studies

(Gholz et al. 1991; Teskey et al. 1994; Clark et al. 2001; Martin & Jokela 2004). SPM-2 simulates hourly fluxes of CO_2 and water, and accounts for the contributions of typical understory components including saw palmetto (*Serenoa repens*), gallberry (*Ilex galabra*) and wax myrtle (*Myrica cerifera*). Annual estimates of net ecosystem carbon exchange simulated by SPM-2 reasonably matched measured values from an eddy covariance flux tower site (Clark et al. 2001).

Although SPM-2 was originally designed to simulate individual stand dynamics, it may be scaled to broad biogeographical extents with inputs of spatially referenced leaf area index (LAI) and stand age. LAI is the ratio of leaf surface supported by a plant to its corresponding horizontal projection on the ground; as such LAI has direct correspondence with the ability of the canopy to absorb light to conduct photosynthesis (Asner & Wessman 1997). Stand age is related to the accumulated biomass and respiration costs of tissue maintenance (Cropper and Gholz 1993).

LAI's contribution as a primary biophysical parameter in NEE simulation also makes it an important indicator of productivity for land managers. Current silvicultural practices focus on improving the availability of resources, through fertilization and herbicidal control of understory, to increase stem growth. Sampson et al (1998) suggest management for increased leaf growth could introduce efficiencies related to site growth potential that would otherwise be missed.

LAI is difficult and expensive to assess *in situ,* resulting in sparse sample sets that are necessarily localized at a stand scale and thus difficult to extrapolate to larger extents (Fassnacht et al. 1997). A model that could accurately determine LAI from remotely sensed data would have the advantage of being spatially explicit, scalable from stand to regional or larger extents, and could sample remote or inaccessible areas (Running et al. 1986). A useful empirical model linking ground-referenced LAI to remote sensing data could also incorporate important local information such as climatological, management, and phenological data.

The generalized southern pine LAI predictive model (GSP-LAI) described in Shoemaker and Cropper (2008) satisfies many of these criteria in that it uses Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imagery to make high resolution (30 m) estimates of LAI for slash and loblolly plantations captured within the image's 185 km wide swath. Climate variables are incorporated in the form of Palmer's Hydrological Drought Index (Karl & Knight 1985) at image date and in various lags; categorical variables representing phenological period and stand data such as age and silvicultural treatments are also included.

With the input of spatially explicit LAI values, NEE may also be simulated for the same extent and resolution using a process-based model. Previous studies have estimated components of NEE with coupled remote sensing and simulation model approaches for diverse forest stands with multiple dominant species (Lucas et al. 2000; Smith et al. 2002; Turner et al. 2004a)). The GSP-LAI model was developed for loblolly and slash pine plantations and the SPM-2 models is limited to closed-canopy slash pine forests (age 8 or older). Slash pine plantations are an important forest type in northern Florida, and the simple forest ecosystem provides the potential for greater precision and for outputs relevant to commercial forestry.

The objectives of this study were to apply the GSP-LAI model to a Landsat ETM+ image of an extensive pine plantation holding in North-Central Florida and estimate 1) slash pine Leaf Area Index and 2) slash pine NEE based on integration with the SPM-2 model.

Materials and methods

Study area and data preparation

The study extent is comprised of a 178 655 ha landscape centered at 29°51.5′ N, 82°10.7′ W near Waldo, Florida USA. This extent contains many classes of land cover/ land use including open water, urban and agricultural. Of specific interest are 11 142 ha of intensively managed slash and loblolly plantation forests which as of image date were closed canopy (8 years old or older). Of this 83% was planted in slash and 17% loblolly pine. Other classes of forest were excluded from analysis including natural regrowth areas, recently cut or planted stands, and stands which contained other species of pine, such as longleaf pine (*Pinus palustris*), or hardwoods.

The study extent was imaged by Landsat 7 Enhanced Thematic Mapper Plus (ETM+) on September 17, 2001 at approximately 11:00 am on a cloudless day. Data resolution was 28.5 m. The image was geographically rectified using a second order polynomial equation with between 30 and 40 ground control points. Rectification error reported as $< \pm 0.5$ pixels.

ETM+ at-sensor reflectance values were integrated with raster-converted stand data provided by Rayonier, Inc. in an overlay procedure within image processing software to maintain location integrity (Leica Geosystems 2003). The resultant value attribute table included date of establishment, planting density and silvicultural treatments, including date of fertilization or herbicide application. Ancillary information such as climatic and phenological data was incorporated in the same manner. The resultant layer stack was reported as a text file with over 150,000 rows of pixel information including coordinates and imported into a Statistica spreadsheet (StatSoft 2004) where it was densified with tassel cap components 1-3 (Huang et al. 2002) in preparation for analysis (Table 1).

Modeling leaf area index

Spatially explicit LAI values were estimated for the plantation pine within the study extent by applying the GSP-LAI model (Shoemaker and Cropper 2008) to the integrated data. The GSP-LAI model was based on Multilayer Perceptron (MLP) architecture (Lui et al. 2003). The Artificial Neural Network consisted of two fully connected hidden layers with 16 and 7 nodes respectively. The MLP was trained using back propagation, in which network weights are modified to reduce error through

gradient descent (Ozesmi et al. 2006). The GSP-LAI model significantly improved LAI estimates for Florida pine species compared to multiple regression models, with an r^2 of 0.77 and an RMSE less than 0.50 for validation data (Shoemaker and Cropper 2008). Python source code for the GSP-LAI model is freely available from the corresponding author. Although stand age in these relatively short rotation pine plantations can be estimated from Landsat image time series (Binford et al 2006), we used stand age data supplied by Rayonier, Inc. in this study. The Artificial Neural Network model predictions of LAI values and stand age were used to generate estimates of NEE using the slash pine specific forest productivity model SPM-2.

Table 1. Input variables for the GSP-LAI Artificial Neural Network Model.

Variable	Tag	Type	Equation/ Bandwidth	Range	Notes
Band 2	B2	Continuous	0.52 – 0.60μm Green	0 – 255	Surface reflectance, 8-byte
Band 3	B3	Continuous	0.60 – 0.63μm Red	0 – 255	Surface reflectance, 8-byte
Band 5	B5	Continuous	1.55 – 1.75μm Mid infrared	0 – 255	Surface reflectance, 8-byte
Band 7	B7	Continuous	2.08 – 2.35μm Mid infrared	0 – 255	Surface reflectance, 8-byte
Tasseled Cap Analysis Component 1	TCA-1	Continuous	0.2043(B1) + 0.4158(B2) + 0.5524(B3) + 0.5741(B4) + 0.3124(B5) + 0.2303(B7)		n-space vegetation index: "Brightness"
Tasseled Cap Analysis Component 2	TCA-2	Continuous	(-0.1603(B1)) + (-0.2819(B2)) + (-0.4934(B3)) + 0.7940(B4) + 0.0002(B5) + (-0.1446(B7))		n-space vegetation index: "Greenness"
Tasseled Cap Analysis Component 3	TCA-3	Continuous	0.0315(B1) + 0.2021(B2) + 0.3102(B3) + 0.1594(B4) + (-0.6806(B5)) + (-0.6109(B7))		n-space vegetation index: "Wetness"
Species	SPP	Categorical	Loblolly = 1 Slash = 0	N/A	Tree species
Fertilizer	FERT	Categorical	Fertilized = 1 Not Fertilized = 0	N/A	Based on previous season
Herbicide	HERB	Categorical	Treated = 1 Untreated = 0	N/A	Maintained understory control
Minimum LAI period	MIN	Categorical	Within Minimum = 1 Other periods = 0	N/A	Minimum leaf biomass; spans ≈ March through April in region
Expanding LAI period	EXP	Categorical	Within Expansion = 1 Other periods = 0	N/A	Increasing leaf biomass; spans ≈ May through June in region
Declining LAI period	END	Categorical	Within needlefall = 1 Other periods = 0	N/A	Minimum leaf biomass; spans ≈ October through February in study area. Implicit in multiple regressions
Palmer Hydrological Drought Index	PHDI	Continuous	Values generated by NOAA	-7.0 – 7.0	Monthly: indicates severity of dry and wet spells; dry negative values, wet positive values, norms ≈ zero
One year lag PHDI	LAG_PHDI	Continuous	Monthly PHDI – 1 year	-7.0 – 7.0	Previous year's PHDI
Expansion period PHDI	EXP_PHDI	Continuous Interactive	Average PHDI for March, April, May	-21.0 –21.0	PHDI during leaf expansion; interacts with phenological period.
Previous season expansion period PHDI	LAG1_PHDI	Continuous Interactive	Lagged Average PHDI for March, April, May	-21.0 – 21.0	PHDI during leaf expansion; interacts with phenological period.
Two consecutive years expansion period PHDI	SUM_PHDI	Continuous Interactive	Sum Lagged Average PHDI for March, April, May	-42.0 – 42.0	PHDI during leaf expansion; interacts with phenological period.

Simulation of net ecosystem exchange

GSP-LAI leaf area values were reported in spreadsheet format and made ready for SPM-2 by 1) masking of non-forest pixel anomalies comprised of negative LAI values, and 2) extraction of slash pine-only values. The GSP-LAI leaf area estimates were generated for a particular date. Slash pine trees in Florida typically have only two cohorts of needles, leading to considerable variation in LAI through the phenological year (Gholz et al. 1991, Cropper and Gholz 1993). The phenology of the cohort of expanding needles (starting March 1) of the new age class and the litterfall from the old age class needles can be modeled with logistic equations (Cropper and Gholz 1993) with the form of:

$$FLAI = \frac{a}{1+e^{b-c\bullet day}} \tag{1}$$

Where, *FLAI* is the fraction of new leaf area at the day of the year (day) or fraction of the cumulative litterfall from the older leaf cohort for that date.

An established chronosequence of slash pine plantations (Gholz and Fisher 1982) was used to estimate the biomass of stems, branches, and coarse roots for a given plantation age. Processing of LAI values and stand age resulted in an estimate of

NEE in Mg·ha^{-1}·a^{-1} for each pixel defined by coordinates. Both NEE and LAI results were imported into a geographic information system (ESRI 2003) and projected as a map.

Results and discussion

Remote estimation of LAI

The GSP-LAI model estimated projected LAI for 10 797 ha of pine plantations. Values ranged from 0 to 3.93 with a mean of 1.06. The SPM-2 NEE simulations are primarily determined by LAI and age of the plantation (Fig. 1). Plantation age is associated with amount of standing biomass and therefore the amount of respiration lost to the atmosphere. Slash pine plantation productivity responds strongly to LAI, which in turn is influenced by site quality and fertilization. Some combinations of age and LAI are not realistic (e.g. an old plantation with very low leaf area). Approximately 1% of the area analyzed exhibited very low LAI values (< 0.1) which were associated with forest edges.

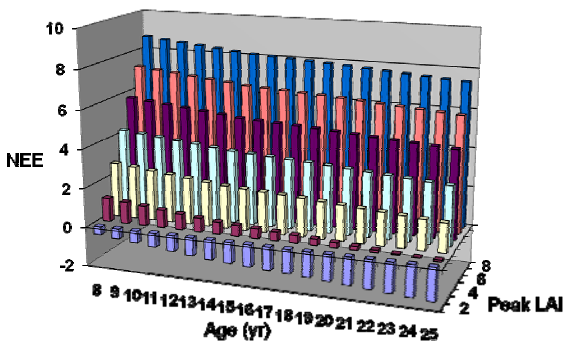

Fig. 1 Simulated response surface of slash pine NEE for plantations between age 8 and 25 years

Fertilization of slash pine stands was reflected by substantial increases in GSP-LAI predicted leaf area compared to unfertilized stands (Fig. 2). Fertilization is known to increase LAI in slash and loblolly (Martin and Jokela 2004); however ground truthing is needed to assess how close model predictions are to observations. Fertilization is a focal treatment in intensive management practices, and indications of canopy response could lead to efficiencies in the location and frequency of application. The availability of reliable LAI data could lead to a paradigm change in management practices were the goal becomes optimization of leaf growth based on site potential.

Leaf area in southern pines is typically estimated through leaf litterfall collection over multiple years or through optical methods associated with estimating canopy light absorption (Gholz et al. 1991). A minimum of two years of leaf litterfall is needed for LAI estimation for a single slash pine stand. Although optical estimation of LAI is more rapid, it depends on assumptions of canopy structure and a model of canopy light absorbance (Chen et al. 1997). Either of the standard techniques depends on field visits to each stand. Estimating LAI from remote sensing (GSP_LAI model) coupled with a model that accurately simulates leaf phenology for NEE estimates (SPM2) provides a mechanism to efficiently manage carbon sequestration over large areas. Stands with low LAI could be identified, and modeling could be used to assess potential costs and benefits of management strategies such as fertilization. These techniques may also play an important role in the problem of verification (Macdicken 1997) of forest carbon sequestration estimates.

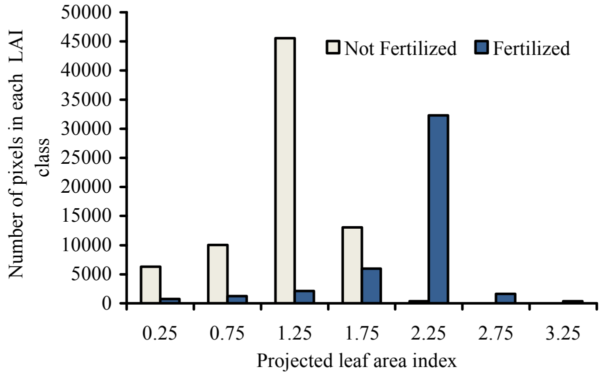

Fig. 2 Effect of variable fertilization on LAI prediction by the GSP-LAI Artificial Neural Network model

Net ecosystem exchange

The SPM-2 model estimated NEE for plantation slash pine totaling 9 770 ha. Values ranged from -5.52 to 11.06 Mg·ha^{-1}·a^{-1} with a mean of 3.47 Mg·ha^{-1}·a^{-1}. As with the LAI values very low NEE was exhibited at forest edges. These estimates are reasonably consistent with multi-year measurements from a Florida Ameriflux study of slash pine forests in north-central Florida (Powell et al. 2008). Total carbon balance for the area analyzed is 33 920 t (3.47 t·ha^{-1}) representing 87 243 t of CO_2. By means of associated map coordinates these values were categorized and displayed on a map along with the Landsat image used as the primary data source (Fig. 3).

The feasibility of estimating forest productivity through coupling remote sensing, site specific data and a process model is clear, but it is difficult to measure accurate ecosystem NEE values for multiple sites over regional scales. Despite our inability to ground-truth, the resultant values for LAI and NEE are plausible and in the realm of expected values. The utility of these estimates is enhanced by their landscape scale and that carbon gain and loss are attributed to specific stands and ownership. These results offer “proof of concept” and further work is encouraged.

Visual analysis of the map (Fig. 3) reveals low LAI and NEE values along logging roads and for other mixed pixels representing partial contributions of forest. These values were not masked as they represent valid data and offer some confidence that the models are selective and appropriate.

The conceptual framework presented here represents one way by which carbon sequestration may be monitored and inventoried, providing necessary underpinning for carbon trading schemes. Landscape-scale valuations of carbon sinks could lead to a re-

valuation of ecosystem services as nations acknowledge the benefits of removing greenhouse gases from the atmosphere.

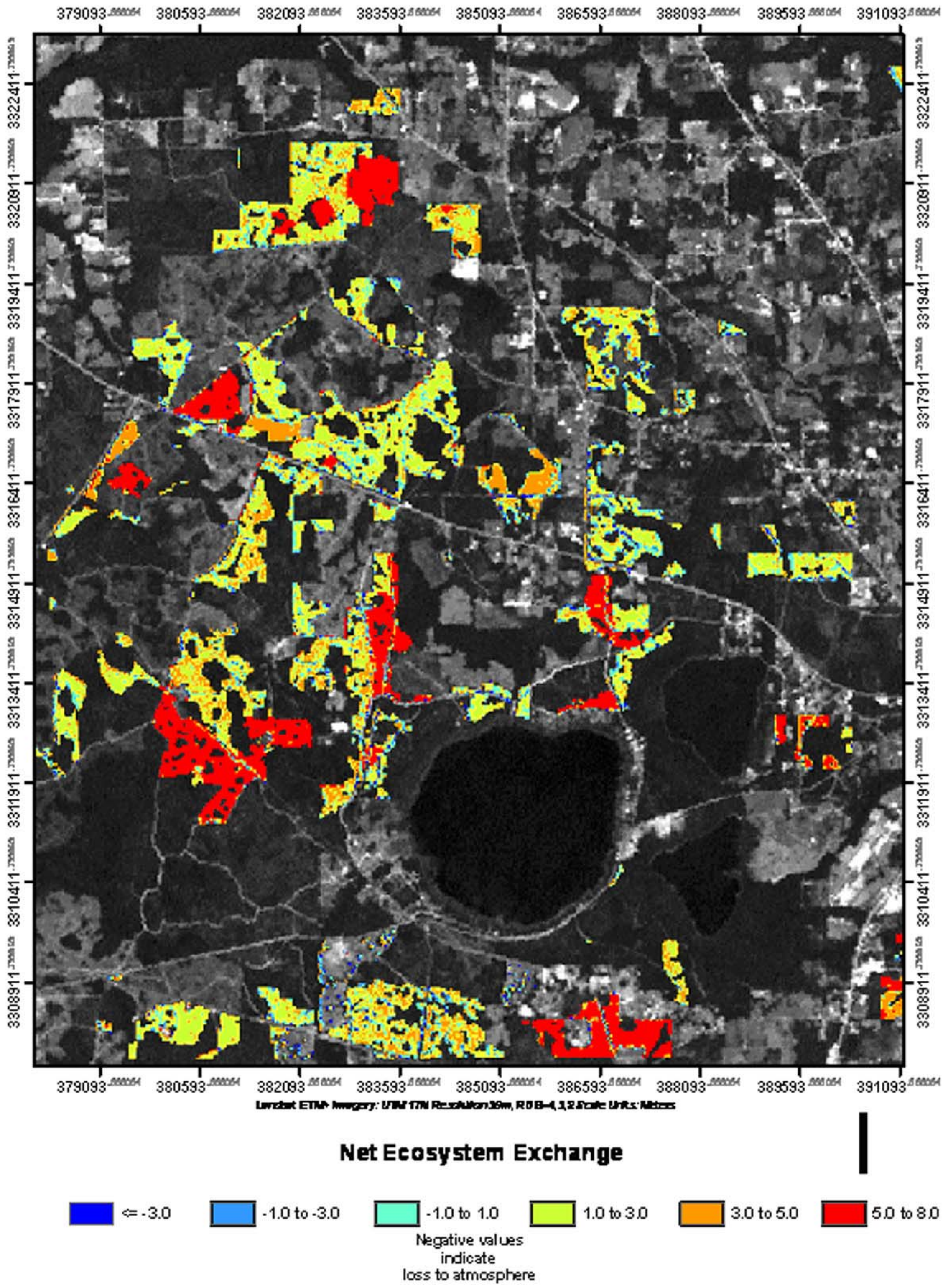

Fig. 3 Predicted NEE values ($\mathrm{Mg \cdot ha^{-1} \cdot a^{-1}}$) for slash pine plantations in north-central Florida for September 17, 2001

Conclusions

This work provides a conceptual model whereby forest productivity may be estimated for a forest system using an empirically derived LAI prediction model and a process simulation model. Spatially explicit results of LAI and NEE values relate important forest attributes to specific stands over large areas creating new opportunities for improved management.

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